**Predicting Food Security with Machine Learning**

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**Abstract**

Hunger is on the rise throughout Africa, with famine threatening millions across several countries. Rapid and accurate identification of food insecurity crises can enable humanitarian responses to mitigate casualties from hunger and save lives. We develop a predictive model of food security based on readily available, spatially granular data on prices, geography, and demographics. Using machine learning techniques, we are able to improve the accuracy of predicting those villages that face a potential threat of hunger. As with any rare event, one challenge with predicting food insecurity is the low rate of severe food insecurity in the baseline data. We use several different approaches to address this imbalance to allow us to capture a higher fraction of these rare events. We apply our procedure to three sub-Saharan African countries: Malawi, Tanzania, and Uganda to predict food security in out-of-sample villages. Bearing in mind the possible spatial-temporal correlations between observations in the training and testing set, we use a nested cross-validation method on year-split data to get a more robust result. We correctly identify up to 40 percent of the most food-insecure clusters, when the baseline model using a logistic regression did not detect any of them. Our result shows that a data-driven model with the help of machine learning methods can significantly improve its performance on capturing the food insecure households despite the imbalance in the data. Our paper demonstrates that this approach could be used in a scalable, automatically updated prediction model that could enhance the current famine early warning systems.

**Keywords:** food insecurity, machine learning, early warning, Sub-Saharan Africa, famine

**Predicting Food Security with Machine Learning**

1. **Introduction**

Hunger crises are increasing in frequency and severity in many parts of the world. Identifying the scale and scope of these crises in a timely and accurate fashion is essential for providing food aid and organizing humanitarian responses to mitigate the long-run effects of food insecurity. Without timely identification to target the vulnerable population, food aid often fails to arrive in the areas in time where the assistance is needed the most (Barrett and Headey 2014). One of the many reasons that prevent building a successful early warning system is that ground truth survey data are scarce, and data collection is costly (Hutchinson 1991). The data gap hinders efforts to effectively target the population in need and calls for the use of data and methods that are cost-effective and accurate. Currently, governments and NGOs in the sub-Saharan Africa region use the Integrated Food Security Phase Classification System (IPC) as the early warning system. The IPC uses a Delphic system that requires detailed on-the-ground data and is updated quarterly for each livelihood zones, making it difficult to identify specific villages that might be at risk of hunger in the near term.

The recent increase in available data on geography, weather, and market price for food staples provides us with the opportunity to predict food security more frequently at a finer geographic level. The use of remotely sensed data to predict socio-economic outcomes is a growing endeavor. Nightlights data (Chen and Nordhaus 2011; Henderson et al. 2012) can serve as a proxy for economic activity, but variations in the nightlight intensity are too low in remote rural or better off urban areas to detect any substantial changes in economic outcomes. Mobile phone data (Blumenstock, Cadamuro, and On (2015); Steele et al., 2017) also hold potential for identifying economic outcomes and are more frequent and less expensive than census surveys. However, geocodes are often limited to cell towers, and the biases associated with using relying on cell phone-sourced information to infer population statistics are as of yet, not well understood. Very high-resolution satellite imagery is becoming cheaper, but the lack of labeled data in the imageries makes it challenging to extract structured information from the raw images (Engstrom et al., 2017; Donaldson and Storeygard, 2016). Recent studies using a Convolutional Neural Network (CNN) and transfer learning (Jean et al., 2016; Babenko et al. 2017) make promising progress utilizing the information in satellite imageries. These models can explain up to 60% - 75% of the variation at the village level wealth and asset measures in several sub-Saharan Africa countries. However, the reliance on the information in the satellite imagery (specifically, building size, roof type, road conditions) limits its performance for time-varying development indicators. Head et al. (2017) find that the prediction performance of the Jean et al. method degrades quickly when applied to health and nutrition outcomes to no better than random guessing in some cases. The reliance on nightlight data in this approach also limits the prediction accuracy when applied in countries with different socioeconomic conditions. The external validity and interpretability of this deep-learning-based approach call for a method tailored for food security predictions.

To the best of our knowledge, Lentz et al. (2019) is one of the few papers that combines publicly available spatially and temporally granular data to predict village-level food security status that significantly improves the prediction accuracy without significant cost in data collection and model training. Building on the framework in Lentz et al. (2019), in this paper, we construct a prototype of an early-warning system that is automatically updated, generalizable, scalable, and cost-effective in predicting areas of potential food shortage. Like Lentz et al., we incorporate data from different sources, dimensions, and scales into a single predictive model of food security status. We use machine learning models to predict cluster-level food security status for targeting aid in times of food shortage. Variables in the model include the market price of food staples, weather shocks in growing seasons, and geospatial features around village clusters. We combine data techniques such as oversampling with the machine learning models to improve the prediction of food insecure categories. The models correctly capture 30-60 % of the most food insecurity categories among the three countries for different food security measures. The main contribution of this paper is to improve the prediction of clusters with the potential food crisis in a setting with imbalanced data. We achieve this by choosing an objective function that balances overall accuracy against the ability to capture the food insecure, along with techniques like data sampling.

Instead of predicting the overall accuracy of food security status in previous studies, this study focuses on correctly detecting the clusters that are food insecure. Similar to a fraud detection problem, severe food insecurity crises are rare but too valuable to miss. The failure of identifying villages with food shortage is more costly than falsely sending food assistance to areas that do not have a shortage of food. Therefore, we focus more on identifying all the insecure clusters to maximize the recall rate in classification, where the recall rate is defined as the percent of truly insecure households correctly captured by the model. We care less about minimizing the number of secure clusters misclassified as unsafe. In technical terms, we put a higher weight on the recall rate than the precision rate for classifying the food security categories. Choosing the right criterion to optimize matters for model selection and parameter tuning. Ultimately, we want the model to correctly detect the minority classes that are food insecure without too many false-positive cases.

Along with choosing the optimization criterion, we also explore the effect of different up and down sampling approaches to identify the food-insecure groups. Various sampling techniques create a balanced dataset that forces the classifiers to learn about the characteristics of the minority class. One such method is oversampling the minority class at the risk of model overfitting. SMOTE creates synthetic new data of the minority class by forming convex combinations of neighboring points, as a way to reduce the overfitting in oversampling.

As a natural extension to Lentz et al. (2019), this study expands the study areas to Malawi, Uganda, and Tanzania with more years of data to test the framework with more heterogeneity in geography, environment, and socioeconomic status. For example, Uganda has two growing seasons, and the main food staples are matoke and cassava, while most areas in Malawi and Tanzania have only one growing season and rely on maize as the staple food. This means adjustments to the local climate and agricultural markets, such as having the weather variables during the local growing seasons, grabbing market data on the staples that take up larger shares in the household budget in that specific region.

The machine learning algorithms and data techniques used for prediction are the same kinds for the three countries, but the hyperparameters are tuned on the training dataset of each country separately. Despite the heterogeneity in socioeconomic and geographic conditions across the three countries, we are able to produce similar prediction results using a unified framework, variables types, and model tuning procedures. This speaks to the validity of the method in expanding to other developing countries with market price data available. At the same time, the model remains flexible and adaptable enough to capture the differences between countries such as climate, crops, and different levels of infrastructure and offer insights on the variables of importance in each country. We compare different methods and protocols for handling the raw data, selecting the optimal model, and setting up parameter tuning procedures to come up with a standardized data flow that maximizes our chances of making the model generalizable for potentially other areas in the world.

This paper uses a data-driven framework with machine learning techniques to predict the onset of food crises. Combined with remote sensing data, household surveys, and price data, the models are able to produce the most spatially and temporally granular predictions of food security. With an emphasis on the structure of the prediction error, this paper uses various machine learning techniques to reduce the misclassification of food insecure clusters. The framework developed in this paper has important policy implications for accurate target and aid areas of potential food shortage in data-scarce environments.

1. **Data:**

***Food Security measurement***

We predict three measures of food security used by the international humanitarian organizations, including USAID and the World Food Programme (WFP): the reduced coping strategies index (rCSI) and the food consumption score (FCS). The FCS gives nutrient-related weighting to the count of different food categories that a household consumes in the past seven days, to come up with a weighted score of food quality. Higher values of the FCS indicate more diversity of nutrition intake and higher food security. The rCSI reflects the number of coping strategies a household uses to address possible food shortages with higher values of the rCSI indicating lower food security. The rCSI is believed to capture inadequate quantities of food consumed, which is consistent with acute food insecurity. In Figure 1, we present the location and distribution of FCS by category in year 2010 for all three countries to give the readers an idea about the relative portions of food insecure villages and where they were.

Governments and international agencies apply cut-offs to categorize food security status rather than use the continuous measure (Vaitla et al., 2017). Consequently, this paper focus on the categorical prediction for the given cutoffs instead of the continuous measures of socio-economic outcomes in previous works (Jean et al., (2016), Steele et al. (2017), and Lentz et al. (2019), among others). The food security category is close to the actual policy scenarios where policymakers are trying to capture all the insecure households in a potential famine year in the currently used IPC system. Our study does not use the household dietary diversity score (HDDS) measure like the other papers do since the variation in the categorical HDDS measure is close to 0, especially after averaging at the cluster level. In other words, a naïve guess that all clusters on average have medium HDDS would beat any models available.

***Explanatory data***

The variables used to predict food security are high-frequency data, including precipitation, temperature, market prices, soil quality, and geographic variables. These data are generally collected remotely and are widely available. A complete list of variables used in model with units and summary stats are presented in Appendix Table A1. We handcrafted weather-related variables such as the first day of rain, length of dry spells, growing degree days, and heating degree days from the raw precipitation and temperature data during the previous growing seasons specific for each country. We gather the market prices for main food grains such as maize, rice, and groundnuts for the major markets in each country and align the villages to the prices in their nearest markets. To help forecast future food security status, we use prices with one to three months prior to the household survey time. The tree-based models help us choose from a variety of price variables of different products, lag length, and format, with more details in the discussion section. For missing data in the market prices, we construct market thinness measures defined as the number of weeks with price information missing in a given month. Variables regarding wealth status, cellphone ownership, and demographic characteristics are created using answers from the LSMS surveys. Cellular phones are access to financial resources, market information, and remittance flow (Eagle et al. 2010, Blumenstock et al. 2016). Although our results rely on these variables collected from the surveys, we use satellite imagery predicted roof types, consumption aggregates, and asset index as proxies for the predictors based on information from the household surveys. Household roof type is used as a crude proxy of poverty that can be accurately captured from satellite imagery.

1. **Methods**

The process of developing a predictive model requires a number of critical decisions. Here we outline the specific decisions made regarding the nature of our target or dependent variable, the criterion used to evaluate the results, the approach to sampling and the machine learning methods used to build the models.

***Categorical vs. continuous measure***

We focus on the categorical prediction for the given cutoffs of each food security measure as it captures the policy scenario where the policymakers need to target communities that are likely to fall under some average food security threshold. We do care about the overall fit of the prediction on the actual food security measures, and we achieve a similar performance of model fit compared to previous studies at around 0.7 R squared. Since this paper focuses on successfully detecting the villages in need of food assistance, we use categorical measures of food security to transform the prediction task into a classification problem. In this way, we can utilize data techniques such as choosing the right result metrics, sampling techniques to improve the chance of detecting insecure villages.

According to the FEWSNET, an FCS from 0 to 28 is considered as “Poor”; 28 to 42 as “Borderline,” and above 42 as “Acceptable. An rCSI above 42 is considered “Severely insecure”; 17 to 42 is “Moderately insecure”; 4 to 17 is “Mildly insecure”; and 0 to 4 is “Food Secure.” These cutoffs used in the fieldwork by NGOs and governments allow us to transform the continuous food security measures into categorical using these cutoffs. The goal of the prediction problem then becomes detecting the clusters in the most insecure category (“Poor” or “severely/moderately insecure”) if there is one. In some cases, these insecure clusters comprise less than 1% in the data which makes it harder to detect using conventional methods (with exact proportion on the entire dataset presented in Appendix Figure A1).

An alternative to strictly following the cutoffs to have three or four categories as outcome variables is to have the outcome variable as binary by treating the safest category as 0, and the rest as “potentially or currently insecure.” The binary split has simple interpretations of the results, and we can use measures like the ROC curve to demonstrate the models’ ability to classify the unsafe category accurately. We use the results on the binary splits to be a coarser classification of clusters that may require assistance. One significant advantage in treating data as binary is that we have more data in the minority class to make the models work better.

***Result metrics***

Predicting when and where the food security crisis will happen is more important than having an accurate assessment of the food security status of the general population. In technical terms, this study focuses on the recall rate of insecure households, rather than the overall prediction accuracy. Models aiming to maximize the overall accuracy tend to capture characteristics that are rich in the majority of the population and fail to understand the insecure households enough. We want to maximize the recall rate to try and get all the insecure households, without a too low precision rate so that we do not mistakenly categorize all the secure households as insecure. The F-1 score, essentially the weighted harmonic averages of precision and recall, serves as balanced measures of the two. To summarize, the prediction results will be evaluated based mainly on recall of the insecure category but also in consideration of the performance of other measures.

In the binary case, we use the widely used measure called receiver operating characteristic (ROC) curve. The curve plots the true positive rate (TPR) or recall against the false positive rate (FPR) at different values of threshold, where the threshold is defined as the probability cutoff of treating an instance as 1. The false-positive rate measures the cases we have a “false alarm.” The area under the ROC curve (AUC) is the universal statistic for model comparison in the machine learning practices.

***Sampling***

Food secure households and villages make up the majority of the data. When we feed the prediction algorithms with training data made up of these proportions, the models naturally better identify the characteristics of the secure households more than the insecure ones. As a result, the models tend to predict villages in the testing dataset to be secure. To force the models to gain as much information as possible about the food-insecure households, we apply downsampling and oversampling techniques to create a more balanced training dataset in terms of the outcome variable while the testing set remains intact. Specifically, we downsample the clusters in the food secure category and oversample the observations that are food insecure to artificially create a training set where the insecure households make up half of the observations. These methods are broadly used to deal with imbalanced datasets. The main disadvantage with oversampling is that by making exact copies of the minority class, the models tend to overfit. We also use methods like SMOTE (Synthetic Minority Oversampling Technique) to creates synthetic new data of the minority class by forming convex combinations of neighboring points as a way to reduce the overfitting in oversampling. Specifically, we use SMOTE-TOMEK, which combines the oversampling method of SMOTE and then under samples the synthetic data with Tomek links to avoid overfitting. Another method we use is ADASYN (Adaptive Synthetic), which adds a random noise in the created synthetic new data.

As an alternative to the sampling technique, the cost-sensitive learning approach penalizes misclassifications of the minority class more heavily by having a cost function, which is equal to the inverse of the class proportions (Elkan 2001). This function produces an extra reward for identifying the minority class over the majority class. This approach penalizes the misclassifications of the minority class more heavily than the misclassifications of the majority class, in hopes that this increases the true positive rate. However, defining the “right” cost is not always easy, and they might vary from one case to another. The sampling approach that we use in this paper can be seen as a wrapper-based method that can make any learning algorithm cost-sensitive. The sampling effectively imposes non-uniform misclassification costs on different categories (Elkan, 2001). Weiss, McCarthy, and Zabar (2007) show that oversampling may be preferable for smaller data sets like ours, and cost-sensitive learning is more suitable for datasets with over 10,000 observations. Based on the reasons listed above, our study chooses the sampling approach over cost-sensitive learning.

***Data split***

In the case of spatial and temporal correlation, splitting the data set into training and testing sets is harder than one would think, as the assumption of independence between the training and the testing set is not easily satisfied. The classical assumption of a random split in generating the testing data set may not hold since the points randomly assigned to the testing may have a strong spatial and temporal correlation with some of the points in the training set. Because of these correlations, models with high prediction accuracy on the training set would appear to have higher than actual accuracy in the testing set as well (Meyer et al. 2018). Consequently, the training process would prefer models and parameters that are complex enough to understand every bit of detail in the training set. These models would tend to overfit in a genuinely independent testing set as is demonstrated in simulation results in Robert et al. (2017). Taking these into consideration, this paper chooses the year split as the data split strategy. In other words, we use one year as the training set to predict food security in another year. Survey data collected in another year or wave have weaker ties with the training data because the time difference is long and that not all villages are repeatedly visited in another year. Spatial correlation between points that are close in space with similarity but are separated into training and testing might create upward bias on the out-of-sample performance. A similar argument can be made for a purely random split method, as the independence assumption of the testing set would no longer be valid.

***Nested cross-validation***

Cross-validation (CV) is a resampling-based technique for the estimation of a model’s predictive performance and is often used in hyper-parameters tuning and model selection. In this paper we use a two-tier nested CV. First, we use any two years of data to predict the other year and average the results on the three test sets to get generalized performance metrics. The reason why we do this is that the number of rare events of food insecurity can vary a lot from one year to another, and the averaging provides a relatively stable performance to understand the generalization error of the underlying model. Also, we apply this stratified CV method to avoid the spatiotemporal correlation issue mentioned above. In the model training phase, we use a K-fold CV grid search for hyper-parameters tuning and model selection. K-fold CV randomly divides the data into K subsets of approximately the same size and then having each subset used successively as the test set.

***Data segmentation***

Data segmentation is another choice to make in defining our training dataset. Due to the heterogeneity of different countries and regions, including more data in the training data, sometimes is adding more noise than information. The concern of fitting a generic model on all the data that we can get our hands on is that the model tends to work well on the country or region that takes up the larger portion of the observations and perform poorly on places with fewer survey data. Especially when combined with the oversampling method, the model fit on the whole sample performs worse in some areas more than the others (with more discussions in the error analysis section). Also, the price variables across countries are not entirely the same, and as a result, we lose a few price variables on some of the grains when we train the model on all the countries. We compare the results of models trained on the entire dataset of three countries, with models trained by each country separately.

***Classification algorithms***

For structured data like ours (unlike unstructured data like text or pure images), tree-based methods are popular, as they work well with the nonlinearities and a large number of variables with different scales in the data. Decision trees also make no distributional assumptions on the data to reduce the misspecification error. We start with a simple machine learning algorithm known as Decision Trees. The decision tree splits the training data based on several input variables, such as does the village undergoes a long dry spell in the last year? If so, is the cluster rural or urban? The splits created by the questions divide the training data into different subsets of data known as the “leaves.” In this classification problem, each leaf is associated with a probability of falling into the secure or insecure category and the probability is trained using the training dataset. The main hyperparameter of the classification trees is the depth of the trees. Deeper trees tend to capture more complexity of the training data but may suffer from overfitting when applied to the testing set. Shallow trees may suffer from losing essential splits in the data and underfit the training set. As a result, tree-based ensemble learning methods like the Random Forest, and Gradient Boosting help improve model performances by averaging and sequentially improving the base trees, which is particularly helpful when there is a large number of potential variables in our model. Random Forest is a kind of bagging algorithm, short for “Bootstrap aggregating.” The idea of the algorithm is to create many deep trees based on randomly selected subsamples of the training data with randomly selected variables determined at each split of the trees (the bootstrap aspect) and then using the weighted average of the results from the trees (the aggregating aspect) to reduce the total variance of the deep trees.

Boosting differs from the bagging method in that trees are grown sequentially instead of in parallel. Modelers usually start with a simple, shallow tree for prediction and then use the error in prediction from the previously grown tree to adjust the weights in the next iteration. Errors are corrected by sequentially adjusting the weights in the existing models until no more improvements can be made. Weiss (2014) suggested that boosting methods tend to perform well at classifying minority examples because boosting places more emphasis on misclassified instances in the training set and the errors are more likely to come from the minority classes. Based on the performance across twenty-nine datasets, Tischio and Weiss (2019) find that models like Decision Trees, Adaboost, and Gradient Boosting perform better than other algorithms in the presence of imbalanced data. The gradient boosted tree improves the initial decision tree model by sequentially adjusting the model in the direction of the negative gradient of the loss function defined as the squared distance of predicted and actual values. The Xgboost (Extreme Gradient Boosting) algorithm relies on the same principles as gradient boosting but is more efficient and faster since it adds regularization to the loss function to prevent overfitting.

***Baseline model***

As a comparator, we use a standard logistic regression as the baseline model. We estimate each country separately using all but the last year of data, and then use the model results to predict the last year, without downsampling or oversampling methods. We use the same variables used in machine learning models such as food prices, market thinness, cellphone ownership, floor/roof material, asset index, length of dry spells, average temperature, and the total amount of rain.

1. **Results**

The results section shows many improvements in the performance of the machine learning models compared to the baseline model. The results suggest that the machine learning algorithms, combined with data techniques, help capture the rare food insecure instances when the conventional methods cannot.

First, we use a binary cutoff of the outcome variable (“safe vs not”) to test the model’s ability to differentiate clusters with those that are relatively better off, and those need attention. The outcome is defined as “not safe” if the food security measurement does not fall into the safest category. At the binary cutoff, we have more observations in the minority class, so the dataset is more balanced and no need for the sampling techniques. Table 1 shows the Nested-CV results of baseline and machine learning models of the binary cutoff. The performances are measured by overall accuracy, recall rate, and F-1 score. Across different measures of food security and country combination, the overall classification accuracy is reasonably high (from 0.55 to 0.84), demonstrating that our framework, in general, predicts food security well. Using a simple logistic regression, we successfully classify 67% to 80% of the clusters in these three countries into safe vs not, with prediction accuracy around 0.60 to 0.84 for FCS measure and around 0.6 to 0.7 for rCSI. Machine learning algorithms outperforms the baseline model in most cases but only slightly. However, for all models, most of these correctly predicted samples come from the food secure categories; the recall rates of the insecure category are a lot lower. Here is where the improvements from the machine learning models are particularly important. While the baseline model is only able to identify 6%- 36% of the observations in ‘not safe’ category, the ML models are correctly picking up 8% to 72%, with higher F-1 scores across the five different cases. This result shows how the ML models are better at picking up characteristics of the minority class.

The results in Table 1 are based on a threshold of 0.5, i.e. if the predicted probability is larger than 0.5, then the cluster would be classified as “not safe.” The ROC curve illustrates how well the model performs when we vary the probability threshold from 0 to 1. Fig. 2 show the results of ROC curves of baseline and machine learning models. The y-axis of the ROC curve shows the recall or true positive rate of correctly identifying a “not safe” cluster (higher the better). The x-axis measures the false positive rate of falsely identifying a safe cluster as not safe (lower the better). Curves that are closer to the top-left corner have better performance, measured in the metric of “area under the curve,” whereas the 45-degree line is equivalent to random guessing. Across five different country-measure combinations, we see the machine learning methods perform much better than the baseline model. Random forest and xgBoost models consistently outperform the baseline model despite the changes in outcome measures and countries, with 0.75 to 0.90 AUC for the FCS measures and 0.67 to 0.71 for rCSI measures. In comparison, the baseline model of logistic regression ranges from 0.6 to 0.67 AUC. The performance of the tree model is more nuanced and unstable in different cases due to overfitting, but all the more reasons to justify the choice of xgBoost and random forest models. This makes sense as these two models achieve better bias-variance combinations using ensemble methods to improve upon the base tree model.

A more practical and challenging problem would be predicting the categories used in fieldwork, such as poor/ borderline/acceptable food consumption scores. Here we refer to them as FEWSNET cutoffs. The emphasis of the model would be to detect the most food-insecure category (in the case of FCS, poor food consumption score), which represents less than 1% to 3% of the training dataset but are of great interest from a policy perspective. The ability to increase our chances of detecting them in an out-of-sample scenario, even slightly, can prove useful in humanitarian warning and aid purposes. Table 2 presents the results of predicting the FEWSNET cutoff categories using ML models using the original imbalanced dataset. The results are cross-validated using any two years to predict the third with the assumption that data in one year is relatively independent of the data in another. The numbers before the forward-slash “/” are the measures for the middle category of food security (i.e. borderline or mildly insecure), and the numbers after the forward-slash are measures about the most food-insecure category (i.e. poor or moderately/severely insecure). The overall accuracy using the FEWSNET cutoff is very much the same as expected for both the baseline and ML models. The recalls for the middle category of food security are also similar. The more interesting finding is how the baseline model is unable to detect any of the most insecure categories across all of the five cases. Even though our machine learning models improve the recall rate for an average of 13% in the binary case, they fail to improve much for the most food-insecure category. In the case of Tanzania and Uganda, the ML models could not identify any of the observations that have poor FCS or are moderately food insecure, and recall of the middle category are relatively low. The models perform slightly better in Malawi with 0.23 and 0.30 recall for FCS and rCSI. F-1 score for the insecure category is also low because of the low recall rate. The main reason for the poor performance mainly comes the low number of severely food insecure observations, or the llack of training data in the minority class. The training data in previous years contain very few cases of food-insecure villages. The majority of the sample is comprised of villages not suffering from imminent danger of hunger. Models, machine learning, or conventional, trained on these data tend to capture more the characteristics of the food secure villages and unable to identify signs in the data that signify food insecure.

As is discussed in the method section, we apply oversampling and downsampling on the training data to create a more balanced dataset. Table 3 shows the results of different sampling techniques combined with different machine learning models, compared to the baseline model with no data sampling applied. Results are shown in using simple oversampling of the minority class, SMOTE-Tomek, and ADASYN respectively. Unlike the results in Table 2, when combined with sampling, the performance difference in machine learning methods and our baseline model diverges. We see an increase in the recall rate in almost all the country-measure combinations in both the middle and most insecure categories. In Malawi, the recall rate on FCS has increased from 0.26 in baseline to 0.26 - 0.38 for the borderline category and from 0 in baseline 0.06 - 0.27 for the poor category; recall rate on rCSI rise from 0.36 in baseline to 0.36 - 0.72 for mildly insecure category and from 0 to 0.04 – 0.20 for the moderately insecure category. In Tanzania, the recall rate on FCS has increased from 0.06 to 0.06 - 0.29 for the borderline category and from 0 to 0.00 - 0.43 for the poor category; recall rate on rCSI increase from 0.29 to 0.29 - 0.54 for mildly insecure category and 0.07 – 0.20 for the moderately insecure category. In Uganda, the performance improvement is small for the borderline category, but the recall rate on the poor category increased from 0 to 0.3. The F-1 scores of all the fives cases are mostly reasonable, with specific numbers presented in Appendix Table A1. The balanced training data have forced models to take up more structures of the data in the insecure category and lead to more correctly identified insecure villages in both the middle and most food-insecure category. There are cost of more misclassification on the secure households (represented by a lower precision) in applying the sampling, but we care more about the recall and F-1 score.

Comparing different oversampling methods, ADASYN, in general, performs better than SMOTE-Tomek as it adds random noise to the oversampled observations to prevent overfitting. The simple oversampling method outperforms ADASYN in the Malawi-FCS case, but in general it performs worse than the other models due to overfitting.

The above results are all based on models trained in each country respectively. One possible check on Data Segmentation is to train the model a combined dataset of three countries and predict all the data in the test datasets. Table 4 presents the result comparison trained on the combined dataset and by country, both using the oversampling methods. Due to the heterogeneity in the data across the country and that some of the variables do not exist for all of the three countries, the model trained on the combined dataset underperforms the counterpart.

1. **Discussion**

***Feature importance analysis***

Interpretability of the models matters. Identifying the variables that are essential to successfully capture insecure households can aid and offer guidance for future monitoring and aid work. Tree-based ML Models such as random forest and gradient boosting provide feature importance parameters as different variables offer different information gains in training the models. Table 5 presents the case of Random Forest model trained on Malawi-FCS, both the model trained on original dataset and the model trained on the dataset after doing the oversampling. In both cases, the assets variables are on top of the list in classifying villages that are safe vs not, such as Number cellphones owned, roof types, floor types, and asset index. Geospatial variables related to distance to outside worlds, such as distance to road and population center, also explain more variations than the others. Weather variables, particularly drought-related (maximum days without rain, and first day of rain) and flood-related (precipitation in flood-prone regions) matters for the prediction. Market variables (Bean/maize prices and nuts market thinness) are more critical in the oversample training set than the original dataset. This result suggests the ability of market prices to better capture characteristics leading to food insecurity.

***Error analysis (TBD)***

* Regional error analysis
* Urban vs. rural
* By food security measure

1. **Conclusion**

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**Fig. 1 Map of FCS in 2010**

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**Fig. 2: ROC curves of Baseline vs. ML algorithms with binary cutoff**

**Table 1: Nested-CV results: ML algorithm V.S. baseline using a binary cutoff**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Country | Food Security Measure | Overall  Accuracy  (Baseline) | Overall  Accuracy  (ML) | Recall Insecure Categories  (Baseline) | Recall Insecure Category  (ML) | F-1 score Insecure Categories  (Baseline) | F-1 score Insecure Category  (ML) |
| Malawi | FCS | 0.71 | 0.74-0.76 | 0.25 | 0.18 - 0.38 | 0.17 | 0.14 – 0.36 |
| rCSI | 0.69 | 0.61-0.63 | 0.36 | 0.54 - 0.72 | 0.36 | 0.48 – 0.56 |
| Tanzania | FCS | 0.81 | 0.82-0.84 | 0.06 | 0.08 -0.29 | 0.07 | 0.12 – 0.39 |
| rCSI | 0.55 | 0.58-0.63 | 0.29 | 0.44 - 0.54 | 0.27 | 0.45 – 0.52 |
| Uganda | FCS | 0.67 | 0.59-0.71 | 0.36 | 0.33 - 0.36 | 0.40 | 0.32 – 0.45 |

**\*** ML results shown in range as the performance of the three models vary slightly

**Table 2: Nested-CV results: ML algorithm V.S. baseline without sampling using FEWSNET cutoff**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Country | Food Security Measure | Overall  Accuracy  (Baseline) | Overall  Accuracy  (ML) | Recall Rate Insecure Categories  (Baseline) | Recall Rate Insecure Category  (ML) | F-1 score Insecure Categories  (Baseline) | F-1 score Insecure Category  (ML) |
| Malawi | FCS | 0.71 | 0.75-0.76 | 0.26 / 0.00 | 0.18 / 0.23 | 0.16 / 0.00 | 0.31/ 0.18 |
| rCSI | 0.69 | 0.60-0.63 | 0.36 / 0.00 | 0.54 / 0.30 | 0.37 / 0.00 | 0. 54/ 0.17 |
| Tanzania | FCS | 0.81 | 0.82-0.84 | 0.06 / 0.00 | 0.08 / 0.00 | 0.03 / 0.00 | 0.28 / 0.00 |
| rCSI | 0.55 | 0.59-0.63 | 0.29 / 0.00 | 0.43 / 0.00 | 0.26 / 0.00 | 0.51 / 0.00 |
| Uganda | FCS | 0.67 | 0.59-0.71 | 0.37 / 0.00 | 0.33 / 0.09 | 0.24 / 0.00 | 0.38 / 0.15 |

\* The numbers before the forward-slash “/” are the measures for the mild or middle category of food security (i.e. borderline or mildly insecure), and the numbers after the forward-slash are measures about the most food-insecure category (i.e. poor or moderately/severely insecure).

**Table 3: Nested-CV recall: ML algorithms V.S. baseline with sampling using FEWSNET cutoff**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Country | Food Security Measure | Recall Rate Insecure Category  (Baseline) | Recall Rate Insecure Category  ML +   ADASYN | Recall Rate Insecure Category  ML + Oversample | Recall Rate Insecure Category  ML+ Smote-Tomek |
| Malawi | FCS | 0.26 / 0.00 | 0.38 / 0.15 | 0.32 /0.27 | 0.26 /0.06 |
| rCSI | 0.36 / 0.00 | 0.72 / 0.20 | 0.54 /0.04 | 0.36/0.20 |
| Tanzania | FCS | 0.06 / 0.00 | 0.29 / 0.43 | 0.18/0.00 | 0.06 /0.00 |
| rCSI | 0.29 / 0.00 | 0.54 / 0.07 | 0.21/0.00 | 0.29 /0.20 |
| Uganda | FCS | 0.37 / 0.00 | 0.36 / 0.30 | 0.31/0.00 | 0.36/0.37 |

**\*** The numbers before “/” are the measures for the mild or middle category of food security (i.e., borderline or mildly insecure), and the numbers after “/” are measures about the most food-insecure category (i.e. poor or moderately/severely insecure).

**Table 4: Data Segmentation Comparisons: by country and combined dataset**

|  |  |  |  |
| --- | --- | --- | --- |
| Overall | Food Security Measure | By country  With oversample and ML | Combined dataset  With oversample and ML |
| Malawi | FCS | 0.38 / 0.15 | 0.00 / 0.00 |
| rCSI | 0.72 / 0.20 | 0.08 / 0.00 |
| Tanzania | FCS | 0.29 / 0.43 | 0.00 / 0.00 |
| rCSI | 0.54 / 0.07 | 0.08 / 0.00 |
| Uganda | FCS | 0.36 / 0.50 | 0.00 / 0.00 |

**Table 5: Random Forests Feature importance of variables in Malawi-FCS**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable**  **(original)** | **Importance** | **Variable (oversample)** | **Importance** |
| Number cellphones | 0.12 | Natural roof | 0.11 |
| Own a cell phone | 0.09 | Own a Cell phone | 0.09 |
| Natural roof | 0.05 | Floor dirt sand | 0.08 |
| Asset index | 0.04 | Number cellphones | 0.05 |
| Month | 0.04 | Iron Roof | 0.04 |
| Floor dirt sand | 0.03 | First day of rain | 0.04 |
| Distance to population center | 0.03 | Bean price | 0.04 |
| Distance to road | 0.03 | Max days without rain | 0.03 |
| Percent of agricultural land | 0.03 | Nuts market thinness | 0.03 |
| Max days without rain | 0.03 | Asset index | 0.03 |
| Bean price | 0.03 | Household head age | 0.03 |
| Distance to ADMARC markets | 0.03 | Maize price | 0.03 |
| Rain in flood region | 0.02 | Distance to the nearest road | 0.03 |

**Appendix:**

**Table A1: Variable list and summary statistics (TBD)**

**Table A2: Nested-CV F-1 score: ML algorithms V.S. baseline with sampling using FEWSNET cutoff**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Country | Food Security Measure | F-1 score Insecure Category  (Baseline) | F-1 score  Insecure Category  ML + Oversample | F-1 score  Insecure Category  ML+ Smote-Tomek | F-1 score  Insecure Category  ML +   ADASYN |
| Malawi | FCS | 0.26 / 0.00 | 0.32 /0.31 | 0.26 /0.07 | 0.38 / 0.18 |
| rCSI | 0.36 / 0.00 | 0.54 /0.07 | 0.36/0.16 | 0.72 / 0.15 |
| Tanzania | FCS | 0.06 / 0.00 | 0.18/0.00 | 0.06 /0.02 | 0.29 / 0.25 |
| rCSI | 0.29 / 0.00 | 0.21/0.00 | 0.29 /0.16 | 0.54 / 0.03 |
| Uganda | FCS | 0.37 / 0.00 | 0.31/0.00 | 0.36/0.24 | 0.36 / 0.27 |

A close up of a logo

Description automatically generated

**Fig. A1. Pie chart of food security categories**

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